

AI for Cybersecurity in Photovoltaic Systems

Presenter: Qinghua Li

Associate Professor and the 21st Century Research Leadership Chair

Dept. of Electrical Engineering and Computer Science

University of Arkansas

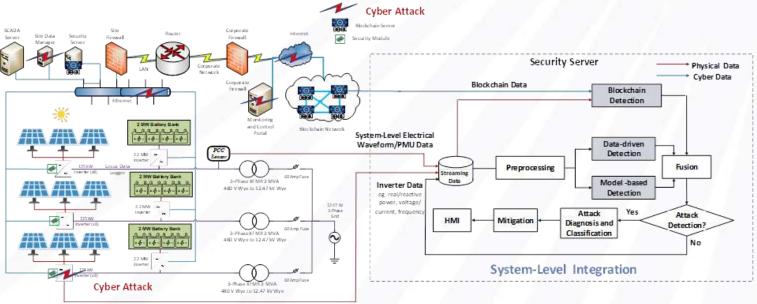
Project: Multilevel Cybersecurity for Photovoltaic Systems (DE-EE0009026)

Principal Investigator: H. Alan Mantooth, University of Arkansas, mantooth@uark.edu

Subawardees: NREL, UGA, UIC, TAMUK, TPI, Ozarks Electric, GE Research, ANL

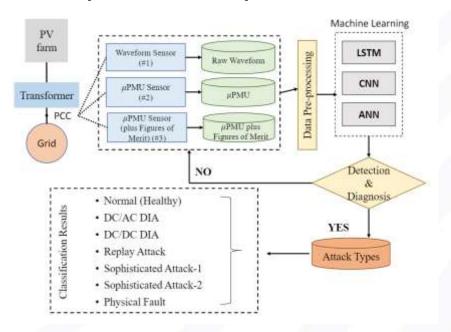
- Inverter-level security
 - Digital twin and hot patching
 - Vulnerability mitigation
 - Attack detection
 - Supply chain security

- System-level security
 - Model- and ML-based attack detection
 - Blockchain-based security



Data-driven Cyberattack Detection

A comprehensive comparison of data-driven cyber-attack detection methods



Neural Network

- Artificial Neural Network (ANN)
- Convolution Neural Network (CNN)
- Long Short-Term Memory (LSTM)

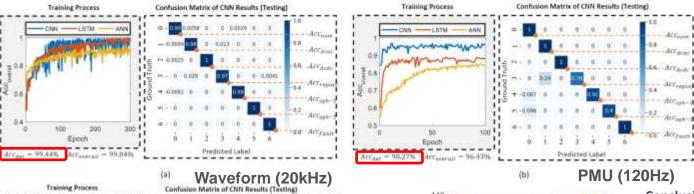
Input Data

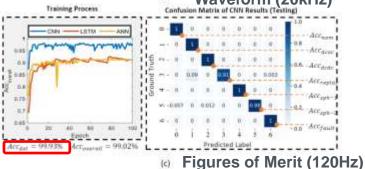
- Type 1: Waveform
- Type 2: μPMU
- Type 3: figure of merit, such as μPMU, THD, unbalanced degree

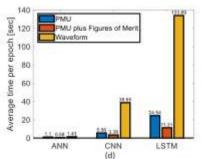
J. Zhang, L. Guo, J. Ye, A. Giani, A. Elasser, W. Song, J. Liu, B. Chen, and H. A. Mantooth, "Machine Learning-based Cyber-attack Detection in Photovoltaic Farms", in *IEEE Open Journal of Power Electronics*, 2023.

Data-driven Cyberattack Detection

A comprehensive comparison of data-driven cyber-attack detection methods







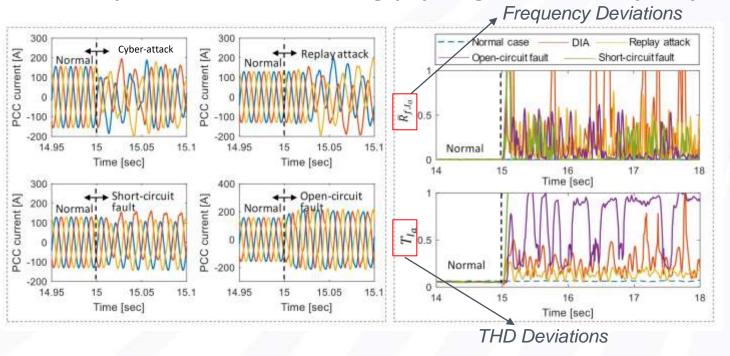
Conclusion:

- Well-designed Figures of Merit outperform the Waveform and PMU data in terms of efficiency and accuracy.
- CNN shows superior performance surpassing ANN and LSTM.
- This method cannot detect novel attacks that are not included in the training set.

J. Zhang, L. Guo, J. Ye, A. Giani, A. Elasser, W. Song, J. Liu, B. Chen, and H. A. Mantooth, "Machine Learning-based Cyber-attack Detection in Photovoltaic Farms", in *IEEE Open Journal of Power Electronics*, 2023.

Data-driven Cyberattack Detection

Data-driven cyber-attack detection using physics-guided time-frequency features

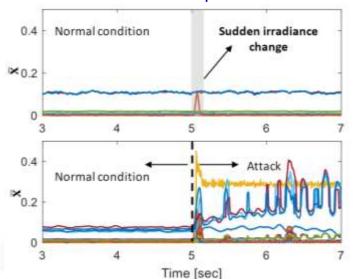


Data-driven Cyberattack Detection

Data-driven cyber-attack detection using physics-guided time-frequency features

Innovative Features to Address New Attacks

Irradiance Impacts

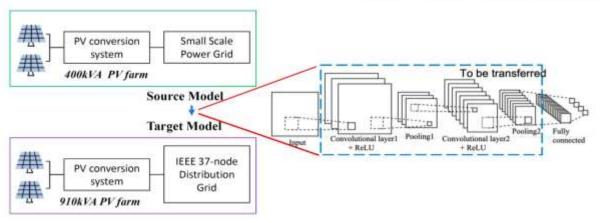


Testing Results when **New Attacks** OCCUI Method-Feature Method-µPMU Accuracy 6 6 6 Validation Training Testing Testing Epoch Epoch Confusion Matrix (Testing) Confusion Matrix (Testing) Ground truth 1434 970 501 2418 431 1717 251 1211 933 257 14 166 366 C1C2C3 C1 CZ C3 Prediction Prediction TN=1434 FP=520 FP=57 TN=970 FN=1 TP=4840 FN=449 TP=4395 REC=99.98%, PRE=98.84%, FPR=3.82% REC=90.73%, PRE=89.42%, FPR=34.90%

L. Guo, J. Zhang, J. Ye, S. J. Coshatt. and W. Song, "Data-driven cyber-attack detection for PV farms via time-frequency domain features," IEEE Transactions on Smart Grid, 2021.

Data-driven Cyberattack Detection

A transfer learning technique for cyber-attack detection in PV farms



- Research problem- how to reduce the data needs and time of training machine learning models for a new solar farm?
- Two solar farm attack models are built to generate the dataset
 - ➤ Solar farm #1: 400 kVA in a small-scale power grid.
 - ➤ Solar farm #2: 910 kVA connected to the IEEE 37-node distributed grid.
- Transfer learning is used

Data-driven Cyberattack Detection

A transfer learning technique for cyber-attack detection in PV farms

Performance comparison between transferred model and the newly trained model

Training samples	F1 (transfered model)	F1 (newly trained model)
10%	0.757	0.673
20%	0.805	0.698
40%	0.912	0.822
60%	0.952	0.894
80%	0.979	0.982
100%	0.978	0.989

Transferred model achieves 95.2% accuracy (F1 score) using 60% training dataset.

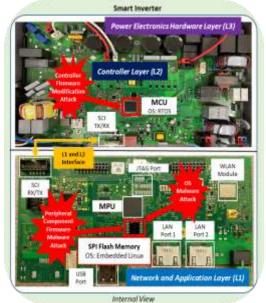
 Transfer learning requires much lower amount of dataset and training time compared with newly-trained model.

Q. Li, J. Zhang, J. Ye and W. Song, "Data-driven cyber-attack detection for photovoltaic systems: A transfer learning approach," 2022 IEEE Applied Power Electronics Conference and Exposition (APEC).

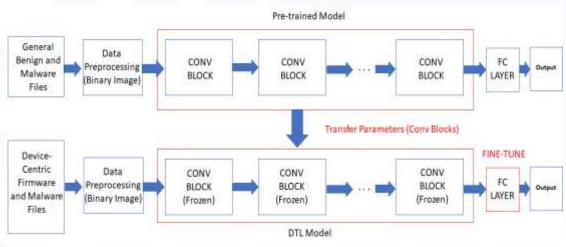


Firmware Malware Detection for Smart Inverters

 The DTL method takes a pre-trained model from a type of image dataset, freeze a portion of the layers, and then fine-tune the last few layers on the newly obtained dataset



A commercial smart inverter architecture



The proposed DTL model

S. Alvee, B. Ahn, S. Ahmad, K. Kim, T. Kim, J. Zeng, "Device-Centric Firmware Malware Detection for Smart Inverters using Deep Transfer Learning," IEEE Design Methodologies Conference (DMC), 2022

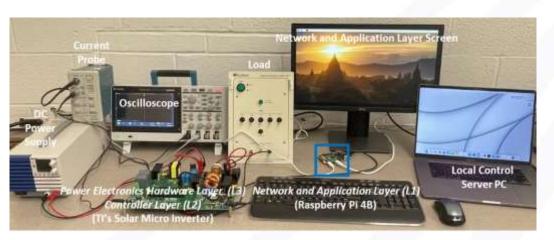
SOLAR ENERGY TECHNOLOGIES OFFICE U.S. Department of Energy

Al in the Project

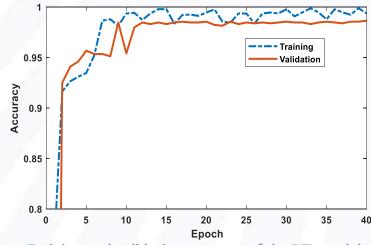
Firmware Malware Detection for Smart Inverters

- The basis DL model experiment
 - 100 benign files and 100 malware

- The proposed DTL model experiment
 - IoT device (Raspberry Pi 4B)
 - 1 benign file and 5 malware







Training and validation accuracy of the DTL model

What We Learned

- ML is a promising technique in PV system cybersecurity
- No ML model works for all
- Lack of data transfer learning might help
 - Transfer across domains
 - Transfer within PV systems
- Physics-informed feature selection could be leveraged
- Cyber attacks and physical faults should be considered together

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- Some content in the slides is shared from Drs. Alan Mantooth, Jin Ye, Taesic Kim, and Chris Farnell.